Impacts of Patch Size and Land-Cover Heterogeneity on Thematic Image Classification Accuracy

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Abstract

Landscape characteristics such as small patch size and land-cover heterogeneity have been hypothesized to increase the likelihood of mis-classifying pixels during thematic image classification. However, there has been a lack of empirical evidence to support these hypotheses. This study utilizes data gathered as part of the accuracy assessment of the 1992 National Land Cover Data (NLCD) set to identify and quantify the impacts of land-cover heterogeneity and patch size on classification accuracy. Logistic regression is employed to assess the impacts of these variables, as well as the impact of land-cover class information. The results reveal that accuracy decreases as land-cover heterogeneity increases and as patch size decreases. These landscape variables remain significant factors in explaining classification accuracy even when adjusted for their confounding association with land-cover class information.

Introduction

Remotely sensed images are being used more extensively than ever to identify land-cover over large regions and to analyze its impacts on environmental conditions (Dobson *et al.*, 1995; Scott and Jennings, 1998). To accurately employ such data, comprehensive knowledge of the causes, location, and extent of classification errors in land-cover data sets is of critical importance (Congalton and Green, 1993; Congalton and Green, 1999; Yang *et al.*, 2000; Shao *et al.*, 2001). Assessing the accuracy of thematic image classification has traditionally been conducted by comparing the map class to the true or reference class at a randomly selected sample of locations. Comparison of the two is conducted by constructing a contingency table, also known as a confusion or error matrix, that reveals discrepancies between the two data sets (Congalton *et al.*, 1983; Story and Congalton, 1986). From this table, a number of measures may be derived to assess the overall accuracy of the classification, including errors of omission and commission, producer's and user's accuracies, and the Kappa coefficient (Congalton and Green, 1999).

Classification error is caused by the interaction of numerous factors, including landscape characteristics, sensor resolution, spectral overlap, preprocessing algorithms, and classification procedures (Campbell, 1983). Landscape characteristics that have been hypothesized to contribute to pixel mis-classification include high land-cover heterogeneity, small patch size, and convoluted shapes, all of which result in pixels being harder to classify and in slight registration differences introducing perceived classification errors. In addition, errors along land-cover boundaries may be compounded because a substantial proportion of the signal, apparently coming from a land area represented by a specific pixel, actually comes from that pixel's neighbors (Townshend *et al.*, 2000). This results in a tendency for mis-classified pixels to form chains along the boundaries of homogeneous patches (Campbell, 1987). Congalton (1988) reported just such a pattern, while analyzing a forest, non-forest classified image. The pattern of a decrease in classification accuracy along patch edges has been assumed in studies of the impact of classification error on landscape metrics (Wickham *et al.*, 1997) and the efficiency of various spatial sampling strategies (Moisen *et al.*, 1994).

Even though the qualitative impacts of contextual landscape characteristics have thus been acknowledged, there is a general lack of precise quantitative information derived from empirical analysis. The purpose of this study is to identify and quantify the impacts of landscape characteristics on whether a pixel is correctly classified and to assess whether these effects are maintained when land-cover information is included in the statistical model. Relationships between classification error and the explanatory variables will be analyzed through the construction of a number of models that allow for individual impacts to be estimated.

Methods

This study utilized data gathered for the accuracy assessment of the National Land Cover Data (NLCD) set, that was initiated by the Multi-Resolution Land Characterization (MRLC) consortium (Loveland and Shaw, 1996). The consortium was created to produce comprehensive, consistently classified land-cover data sets for the United States, one of which is the NLCD. This data set was derived from Landsat Thematic Mapper (TM) images of the contiguous United States (Vogelmann *et al.*, 1998; Vogelmann *et al.*, 2001). Accuracy assessments of the data are being undertaken by federal region, with this study utilizing data gathered for the assessment of Regions 1 through 4, generally the eastern United States (Figure 1). Methodology employed in the assessments has been described in Stehman *et al.* (2000), Yang *et al.* (2000), and Zhu *et al.* (1999; 2000), with the results summarized in Yang *et al.* (2001).

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Photogrammetric Engineering & Remote Sensing
Vol. 68, No. 1, January 2002, pp. 65–70.

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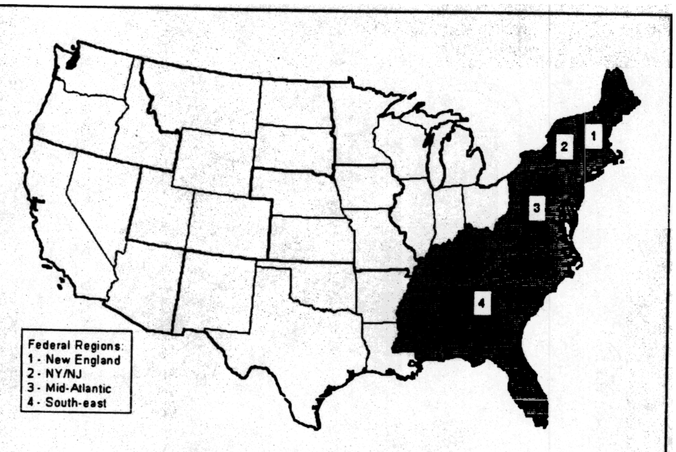

Figure 1. Area under study.

In each of the four regions, accuracy assessments were conducted by a different team of photointerpreters using hardcopy National Aerial Photography Program (NAPP) photographs as the reference data set. To minimize the effects of regional differences in photointerpreter knowledge and experience, data from the four regions were analyzed separately. Table 1 lists the number of samples employed for each class.

Landscape Variable Derivations

Spatial analyses were performed using ARC/INFO, with the four land-cover data sets, one for each region, in the form of ARC/INFO grids. The original NLCD pixel size of 30 meters was retained throughout the study, thus limiting the variables analyzed to the scale of the TM imagery. Four regional sample-point coverages were also utilized, with each point being the centroid of a randomly selected pixel. In order to limit the size of the derived land-cover data sets, buffers with a radius of 3000 meters were created around the sample points. These buffers were then overlayed upon the land-cover grids in order to isolate land-covers in close proximity to the sample points. This resulted in circular zones of land-cover 200 pixels across, centered on all of the sample points. Buffers which exceeded the boundaries of the land-cover grids had their sample points excluded from further analysis. The number of samples remaining for analysis varied from 1009 in Region 3 to 1378 in Region 1 (Table 1).

Once the buffer land-cover grids were created, the patch size and land-cover heterogeneity variables were derived. Patch size was defined as the number of contiguous pixels of the same land-cover class, within which the sample point was located. Contiguity was identified as occurring when any of the eight surrounding pixels were the same class as the center pixel. The other landscape variable, land-cover heterogeneity, was defined as the number of land-cover classes occurring in a three- by three-pixel window centered on the sample pixel. A heterogeneity value greater than one would indicate that the sample was located 30 meters from a patch edge. Theoretically, the maximum heterogeneity value would be nine, a different class in every pixel; however, values in this study varied from one (a homogeneous 3 by 3 block) to seven. Once these variables were identified, an arc macro language (AML) program was employed that identified the NLCD land-cover, patch size, and pixel heterogeneity at the sample points for all four regions. This program extracted the x and y coordinate values from the point coverages and then applied them to identify the grid attributes at those locations.

Statistical Analyses

After the spatial queries were completed, the variables were prepared for use in the statistical analyses. Preliminary analyses indicated that transforming patch size to a logarithmic (base 10) scale would improve the linearity of the logistic regression model. All modeling was conducted with the transformed patch size variable, and any subsequent reference to patch size in these analyses should be understood as pertaining to the logarithm of patch size. Patch size was denoted as explanatory variable x_1, with the other landscape variable, heterogeneity denoted as x_2. In addition, another variable representing the product of heterogeneity and patch size, x_1x_2, was created for use in assessing the importance of their interaction in the logistic regression models. Several of the models also included land-cover class in the set of incorporated explanatory variables. In order to accomplish their inclusion, binary (i.e., dummy) variables were created for each land-cover class, with the variable defined as 1 if the sample pixel belonged to that class and 0 if it did not. Fourteen land-cover classes were incorporated (see Table 1) into the analyses, represented by 13 dummy variables (denoted x_3 through x_{15}).

The final variable created was the binary response variable, representing whether the sample pixel was correctly classified (coded as 1), or not (coded as 0). A correct classification occurred when the photointerpreted class matched the class of the NLCD sample pixel. This definition of agreement applied to the data analyzed represents the strictest definition employed among the various definitions considered for the NLCD accuracy assessment (Yang *et al.*, 2000; Yang *et al.*, 2001).

Logistic regression analysis models the relationship between a binary response variable and one or more explanatory variables (Hosmer and Lemeshow, 1989; Agresti, 1996).

TABLE 1. NUMBER OF SAMPLES BY CLASS PER REGION

Class Name	MRLC Code	Region 1	Region 2	Region 3	Region 4
Low density residential					
High density residential					
Commercial/Industrial/Transportation					
Bare rock/sand					
Quarries/mines					
Transitional					
Deciduous forest					
Evergreen forest					
Mixed forest					
Pasture/hay					
Row crops					
Urban/recreational grasses					
Woody wetlands					
Emergent herbaceous wetlands					
Total Samples					

Results from the regression include the probability of each sample being correctly classified and a number of diagnostic measures to assess the fit of the model and the impact of individual variables. Recent examples of logistic regression applications to remote sensing problems include studies of forest fire ignition (Koutsias and Karteris, 1998; Perestrello de Vasconcelos *et al.*, 2001), deforestation (Ludeke *et al.*, 1990; Chomitz and Gray, 1996; Mertens and Lambin, 2000), and urbanization (Gunter *et al.*, 2000). The logistic regression model is

$$\log\left(p/(1-p)\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \quad + \beta_k x_k$$

where p is the probability of a correct classification, α is the intercept, x_1 through x_k are explanatory variables, and β_1 through β_k the parameters.

Assessment of the effects of the different explanatory variables on accuracy is predicated on the analysis of several logistic regression models (Table 2). Relevant statistics derived from the analyses include the estimates of the β parameters for each model, -2 log likelihood (-2LL), Akaike Information Criterion (AIC), and concordance values. The -2LL statistics are used to test whether all regression coefficients in a model are simultaneously zero, with a significant p-value (<0.05), providing evidence that at least one of the regression coefficients among the explanatory variables in the model is non-zero. Based on the -2LL, the AIC modifies its values by penalizing the model for incorporating marginal, or insignificant, explanatory variables and is a useful measure for comparing different models. For both measures, the lower the value, the better the model. Another advantage of the -2LL statistic is that it can be used to formally test if incorporating additional independent variables results in a statistically significant improvement in model accuracy. Assessment of the additional variables is conducted by calculating the difference between the -2LL values of the two models. This difference follows a chi-square distribution with degrees of freedom equal to the difference in the number of explanatory variables used in the larger model, as compared to the reduced model (Hosmer and Lemeshow 1989, Section 2.4).

Effectiveness of different models can also be analyzed by comparing their concordance values. Concordance is calculated by comparing the probabilities of all of the correctly classified pixels with the probabilities of all of the incorrectly classified pixels (Hosmer and Lemeshow, 1989). If the correctly classified pixel of the pair has the higher probability of being correct, then that pair is said to be concordant; conversely, if the incorrectly classified pixel has the higher probability, then the pair is said to be discordant. Finally, if the probabilities are equal, the pair is said to be tied. Thus, the higher the concordance, the better the model. It should be noted that concordance is used here to compare the models, not to establish the predictive performance of specific models. To quantify a model's ability to predict (in a future sense) whether a given pixel will be classified correctly, a sample of pixels independent of those used to fit the model should be assessed.

To identify the individual impacts of the landscape variables (see Models 1a and 1b, Table 2) on classification accuracy, two additional statistics were computed. The odds ratio, $p/(1-p)$, quantifies the change in the odds of a correct classification, given a one unit change in the explanatory variable. Also computed was the "median effective level," which is the value of the explanatory variable at which each outcome (correct and incorrect classification) has a 50 percent chance of occurring (Agresti, 1996, pp. 104–105). For example, the median effective level for heterogeneity would be its value at which the probability of a correct classification is 0.5. Median effective level is computed as $x = -\alpha/\beta$, where α and β are the parameter estimates from the single variable logistic regression models (Models 1a and 1b).

TABLE 2. DESCRIPTION OF MODELS EVALUATED

Model Number	Model	Description
	β_0	Intercept only
	$\beta_0 + \beta_1 x_1$	Patch size
	$\beta_0 + \beta_2 x_2$	Heterogeneity
	$\beta_0 + \beta_1 x_1 + \beta_2 x_2$	Patch size and heterogeneity
3	$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{1,2} x_1 x_2$	Patch size, heterogeneity and interaction
4	$\beta_0 + \beta_3 x_3 + \beta_4 x_4 + \ldots + \beta_{15} x_{15}$	Land cover
5	$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \ldots + \beta_{15} x_{15}$	Landscape and land cover

Results and Discussion

The goal of the study was to assess the impact of landscape characteristics on thematic image classification accuracy. Models 1a and 1b were developed to assess the individual impacts of land-cover heterogeneity and patch size on classification accuracy. Parameter estimates, odds ratios, and median effective levels from these two models are presented, by region, in Table 3. Both variables were consistently statistically significant ($p < 0.0001$) across all four regions, with the values having opposite effects on classification accuracy. Land-cover heterogeneity had negative slope estimates and odds ratios less than 1, indicating a relationship in which accuracy decreases as heterogeneity increases. Analysis of both the slope estimates and the odds ratios shows remarkable similarity among the four regions for the heterogeneity only model (Model 1b). Median effective levels ranged from a low of 1 (a thematically homogeneous 3 by 3 window) in Region 1 to a high of 1.57 in Region 2. Consequently, when heterogeneity is greater than 1, the probability of a correct classification falls below 0.5. Figure 2 displays the correct classification rate at various heterogeneity values and reflects the almost continuous decrease in accuracy as heterogeneity increases.

In contrast to the heterogeneity model, patch size had positive slope estimates and odds ratios greater than 1, indicating a relationship in which classification accuracy increases as patch size increases. The patch size models displayed slightly greater regional variability than did the heterogeneity relationship, mainly due to the Region 2 estimates. Median effective levels for patch size ranged from 3.36 in Region 4 to 3.80 in Region 3. If we specify 3.5 (equivalent to 3162 pixels, or approximately 284.6 hectares) as a typical median effective level, we have a 50-50 chance of classifying a pixel correctly if the sample pixel is contained in a patch of that size. Samples in patches smaller than this amount have less than a 50 percent chance of being correctly classified, while larger patches have a greater chance. Regional classification accuracies range from 15 to 25 percent for patches less than ten pixels, to 52 to 62 percent for patches greater than 10,000 pixels (Figure 3). Though there is an increasing trend for all of the regions, the magnitude of the impact varies among the regions at specific variable values. Region 2 experiences large increases in accuracy at relatively small sizes, while Region 3 experiences large increases at larger sizes.

Analysis of the AIC values and concordance statistics (Table 4) for the two variables reveals that patch size provides a better single variable model than does heterogeneity (AIC was lower and concordance higher for Model 1a as compared to Model 1b). The exception was Region 2, which had a lower AIC value for heterogeneity than for patch size. Overall, these findings suggest that patch size was a slightly more important determinate of classification accuracy than was heterogeneity.

TABLE 3. EVALUATION OF ORIGINAL LANDSCAPE VARIABLES

		Parameter Estimates		95% Profile Likelihood Confidence Limits of the Odds Ratio			
Region	Explanatory Variable	Intercept α	Slope β	Lower	Median	Upper	Median Effective Level $EL_{50} = -\alpha/\beta$
	Heterogeneity						1.00
	Patch Size						3.55
2	Heterogeneity						1.57
	Patch Size						3.66
	Heterogeneity						1.05
	Patch Size						3.80
4	Heterogeneity						1.40
	Patch Size						3.36

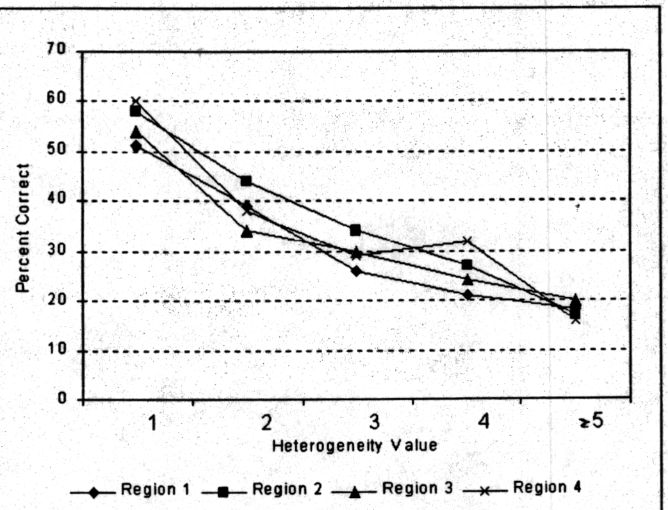

Figure 2. Impact of landscape heterogeneity on classification accuracy.

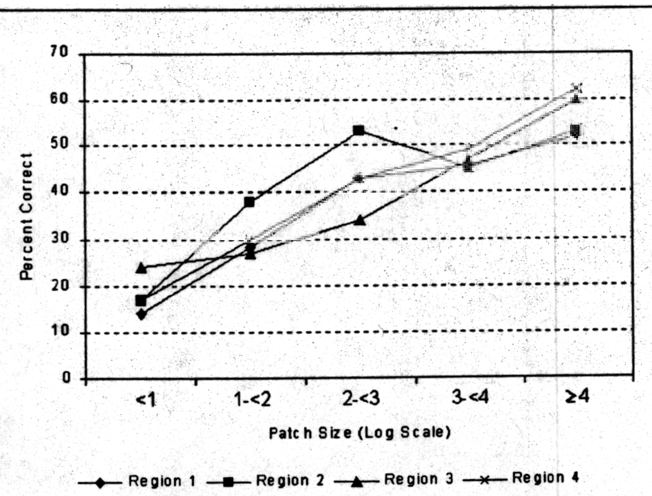

Figure 3. Impact of patch size on classification accuracy.

Now that the impacts of the individual landscape variables have been identified and found to be significant determinates of classification accuracy, the next part of the study assesses whether their significance is maintained when other explanatory variables are added. Six hypothesis tests were developed to examine differences in -2LL values (Table 5). Results from the first hypothesis, H_{01}, indicate that a model incorporating both landscape variables is a significant predictor of accuracy. Because patch size and heterogeneity were correlated (correlations range from -0.51 to -0.59 in the four regions), it is possible that the two landscape variables contribute overlapping information to classification accuracy. To evaluate this possibility, hypotheses H_{02} and H_{03} were developed to test whether patch size provided significant information on classification accuracy in the presence of heterogeneity and vice versa. In all four regions, the individual landscape variables remained statistically significant for Model 2. Consequently, we can state that each landscape variable individually contributed useful information, even when it was adjusted for that portion of explanatory ability it shared with the other landscape variable. Analysis of the -2LL, AIC, and concordance values (see Table 4) also indicated that the combination of the two landscape variables provides a statistical improvement over either of the single variable models.

Addition of the interaction term however, was not found to be statistically significant, except in Region 3 (see Table 5, H_{04}). The significant interaction in Region 3 was accompanied by only a small change in AIC values between Models 2 and 3 (see Table 4), which suggests that its contribution to explaining classification accuracy was relatively weak.

The last two models, Model 4 and Model 5, were developed to evaluate the impact of land-cover and landscape information on classification accuracy. These models assess whether the observed significant relationship between the landscape variables and accuracy was maintained in the presence of land-cover class information (i.e., were the landscape variables simply acting as surrogates for the true determinate of accuracy, land-cover class). Hypothesis H_{05} (see Table 5) evaluated whether the landscape variables contributed significant explanatory value beyond that provided by land-cover class, as captured by dummy variables $x_3, \ldots, x_{15}$. The highly significant test results for H_{05} in all four regions provide strong evidence that the landscape variables were important determinates of accuracy, even adjusted for their shared contribution with land-cover class. In other words, the importance of the landscape variables is not solely attributable to an association between landscape properties and land-cover class. Additionally, the question was reversed in order to analyze whether land-cover class remained an important factor in accuracy assessments when it was adjusted for its association with the landscape variables. The statistically significant results in all four regions for hypothesis H_{06} (see Table 5) demonstrated that land-cover class was still an important determinate of accuracy in a model that already contained the landscape variables.

Combining the outcomes of tests H_{05} and H_{06}, we can state that both land-cover class and landscape characteristics contribute important explanatory information to the logistic

TABLE 4. LOGISTIC REGRESSION MODEL FIT STATISTICS

		Model						
		0	1a	1b	2	3	4	5
Region 1	−2LL	1767.33	1645.35			1630.73	1645.18	1505.83
	AIC	1769.33	1649.35			1638.73	1673.18	1537.83
	Concordance	N/A	67.4			68.4	61.9	74.9
Region 2	−2LL	1737.98	1702.06			1677.38	1569.16	1496.05
	AIC	1739.98	1706.06			1685.38	1597.16	1528.05
	Concordance	N/A	58.2			62.2	63.2	74.7
Region 3	−2LL	1346.34	1288.40			1270.58	1273.78	1203.10
	AIC	1348.34	1292.40			1278.58	1301.78	1235.10
	Concordance	N/A	63.8			65.3	59.5	70.4
Region 4	−2LL	1850.10	1716.87			1704.02	1735.84	1595.32
	AIC	1852.10	1720.87			1712.02	1763.84	1627.32
	Concordance	N/A	67.4			68.5	62.6	73.9

All models produced p-values < 0.0001 for the test of the null hypothesis that all parameters (βs) in the model are simultaneously zero.

regression model of classification accuracy. Based on AIC values and concordance statistics (see Table 4), in three of the regions, the landscape variables (Model 2) provided a slightly better model than did the land-cover class variables (Model 4). The lone exception was Region 2, which had the land-cover class variables providing the better model. Overall, these comparisons suggest that the landscape variables possessed a slightly stronger relationship with classification accuracy than that provided by the land-cover class variables alone.

Conclusions

The goal of this study was to quantify the effects of two landscape variables-land-cover heterogeneity and patch size-on thematic image classification accuracy, and to assess their relative contributions to accuracy in the presence of land-cover information. A total of 5,020 photointerpreted assessment points, distributed across the eastern United States, were analyzed. Results indicate that, at the spatial resolution of the imagery employed, both landscape variables play an important role in determining whether sample pixels were accurately classified. As heterogeneity increases, the probability of misclassifying pixels also increases while, as patch size increases, this probability decreases. The important contribution of the landscape variables in explaining classification error is maintained even when land-cover information is included in the logistic regression model. That is, the two landscape variables remain important explanatory variables even when adjusted for their confounding effects shared with the variables representing land-cover class information. In all four regional data sets analyzed, the best results were produced by a model that combines both landscape and land-cover variables.

The results of this study provide support for the belief that examining pixels in the context of the landscape provides accuracy information beyond that readily apparent by examining an error matrix alone. Landscape characteristics should be awarded the same concern and consideration in accuracy assessments as land-cover class. Additionally, logistic regression has been shown to be a useful tool in allowing for variables beyond land-cover class to be evaluated in terms of their effects on classification accuracy. Future research will focus on how the impacts of landscape variables may vary among land-cover class, photointerpreter characteristics, and the scale at which the variables are derived.

Acknowledgments

The U.S. Environmental Protection Agency funded and conducted the research described in this paper. It has been subject to the Agency's programmatic review and has been approved for publication. Mention of any trade names or commercial products does not constitute endorsement or recommendation for use. The author's would like to thank three anonymous reviewers for their helpful comments. In addition we would like to thank the photographic interpreters who aided in the land-cover classification accuracy assessment.

TABLE 5. CHI-SQUARE TEST STATISTICS FOR MODEL COMPARISONS

Null Hypothesis	Description	Degrees of freedom	Difference in Chi-square Values			
			Region 1	Region 2	Region 3	Region 4
H_{01}		2				
H_{02}		1				
H_{03}						
H_{04}		1				
H_{05}		2				
H_{06}		13				

*-statistically significant at the .05 level

Explanation of hypothesis tests:

$H_{01}:\beta_1 = \beta_2 = 0$ in Model 2. Is the joint contribution of patch size and heterogeneity significant?

$H_{02}:\beta_1 = 0$ in Model 2. Is the additional explanatory contribution of patch size to a model already containing heterogeneity significant?

$H_{03}:\beta_2 = 0$ in Model 2. Is the additional explanatory contribution of heterogeneity to a model already containing patch size significant?

$H_{04}:\beta_{12} = 0$ in Model 3. Does the interaction between patch size and heterogeneity contribute significant explanatory value?

$H_{05}:\beta_1 = \beta_2 = 0$ in Model 5. Is the additional explanatory contribution of the landscape variables to a model already containing the land-cover dummy variables statistically significant?

$H_{06}:\beta_3 = \beta_4 = \ldots = \beta_{15} = 0$ in Model 5. Is the additional explanatory contribution of the land-cover variables to a model already containing the landscape variables statistically significant?

References

Agresti, A., 1996. *An Introduction to Categorical Data Analysis*, John Wiley and Sons, New York, N.Y., 290 p.

Campbell, J.B., 1983. *Mapping the Land: Aerial Imagery for Land Use Information*, Association of American Geographers, Washington, D.C., 97 p.

———, 1987. *Introduction to Remote Sensing*, Guilford Press, New York, N.Y., 622 p.

Chomitz, K.M., and D.A. Gray, 1996. Roads, land use, and deforestation: A spatial model approach to Belize, *World Bank Economic Review*, 10:487–512.

Congalton, R.G., 1988. Using spatial autocorrelation analysis to explore the errors in maps generated from remotely sensed data, *Photogrammetric Engineering & Remote Sensing*, 54(5):587–592.

Congalton, R.G., and K. Green, 1993. A practical look at the sources of confusion in error matrix generation, *Photogrammetric Engineering & Remote Sensing*, 59(5):641–644.

———, 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, Lewis Publishers, Boca Raton, Florida, 137 p.

Congalton, R.G., R.G. Oderwald, and R.A. Mead, 1983. Assessing Landsat classification accuracy using discrete multivariate statistical techniques, *Photogrammetric Engineering & Remote Sensing*, 49(12): 1671–1678.

Dobson, J.E., E.A. Bright, R.L. Ferguson, D.W. Field, L.L. Wood, K.D. Haddad, H. Iredale III, J.R. Jensen, V.V. Klemas, R.J. Orth, and J.P. Thomas, 1995. *NOAA Coastal Change Analysis Program (C-CAP): Guidance for Regional Implementation*, NOAA Technical Report, Department of Commerce, Washington, D.C., NMFS 123, Seattle, Washington, 92 p.

Gunter, J.T., D.G. Hodges, C.M. Swaim, and J.L. Regens, 2000. Predicting the urbanization of pine and mixed forests in Saint Tammany parish, Louisiana, *Photogrammetric Engineering & Remote Sensing*, 66(12):1469–1476.

Hosmer, D.W., and S. Lemeshow, 1989. *Applied Logistic Regression*, John Wiley and Sons, New York, N.Y., 307 p.

Koutsias, N., and M. Karteris, 1998. Logistic regression modeling of multitemporal Thematic Mapper data for burned area mapping, *International Journal of Remote Sensing*, 19(18):3499–3514.

Loveland, T.R., and D.M. Shaw, 1996. Multiresolution land characterization: building collaborative partnerships, *Gap Analysis: A Landscape Approach to Biodiversity Planning Proceedings of the ASPRS/GAP Symposium*, (J.M. Scott, T. Tear, and F. Davis, editors), 15–19 July, Charlotte, North Carolina, National Biological Service, Moscow, Idaho, pp. 83–89.

Ludeke, A.K., R.C. Maggio, and L.M. Reid, 1990. An analysis of anthropogenic deforestation using logistic regression and GIS, *Journal of Environmental Management*, 31:247–259.

Mertens, B., and E.F. Lambin, 2000. Land-cover-change trajectories in southern Cameroon, *Annals of the Association of American Geographers*, 90(3):467–494.

Moisen, G.G., T.C. Edwards, Jr., and D.R. Cutler, 1994. Spatial sampling to assess classification accuracy of remotely sensed data, *Environmental Information Management and Analysis: Ecosystem to Global Scales* (W.K. Michener, J.W. Brunt, and S.G. Stafford, editors), Taylor and Francis, London, England, pp. 159–176.

Perestrello de Vasconcelos, M.J., S. Silva, M. Tome, M. Alvim, and J.M.C. Pereira, 2001. Spatial prediction of fire ignition probabilities: Comparing logistic regression and neural networks, *Photogrammetric Engineering & Remote Sensing*, 67(1):73–81.

Scott, J.M., and M.D. Jennings, 1998. Large-area mapping of biodiversity, *Annals of the Missouri Botanical Garden*, 85:34–47.

Shao, G., D. Liu, and G. Zhao, 2001. Relationships of image classification accuracy and variation of landscape statistics, *Canadian Journal of Remote Sensing*, 27(1):33–43.

Stehman, S.V., J.D. Wickham, L. Yang, and J.H. Smith, 2000. Assessing the accuracy of large-area land cover maps: Experiences from the Multi-Resolution Land-Cover Characteristics (MRLC) project, *Proceedings of the Fourth International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences* (G.B.M. Heuvelink and M.J.P.M. Lemmens, editors), 12–14 July, Amsterdam, The Netherlands, pp. 601–608.

Story, M., and R.G. Congalton, 1986. Accuracy assessment: A user's perspective, *Photogrammetric Engineering & Remote Sensing*, 52(3):397–399.

Townshend, J.R.G., C. Huang, S.N.V. Kalluri, R.S. DeFries, and S. Liang, 2000. Beware of per-pixel characterization of land cover, *International Journal of Remote Sensing*, 21(4):839–843.

Vogelmann, J.E., S.M. Howard, L. Yang, C.R. Larson, B.K. Wylie, and N. Van Driel, 2001. Completion of the 1990s National Land Cover Data Set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources, *Photogrammetric Engineering & Remote Sensing*, 67(6):650–662.

Vogelmann, J.E., T. Sohl, and S.M. Howard, 1998. Regional characterization of land cover using multiple sources of data, *Photogrammetric Engineering & Remote Sensing*, 64(1):45–57.

Wickham, J.D., R.V. O'Neill, K.H. Riitters, T.G. Wade, and K.B. Jones, 1997. Sensitivity of selected landscape pattern metrics to land-cover misclassification and differences in land-cover composition, *Photogrammetric Engineering & Remote Sensing*, 63(4):397–402.

Yang, L., S.V. Stehman, J.H. Smith, and J.D. Wickham, 2001. Thematic accuracy of MRLC land cover for the eastern United States, *Remote Sensing of Environment*, 76:418–422.

Yang, L., S.V. Stehman, J.D. Wickham, J.H. Smith, and N.J. Van Driel, 2000. Thematic validation of land cover data of the eastern United States using aerial photography: feasibility and challenges, *Proceedings of the Fourth International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences* (G.B.M. Heuvelink and M.J.P.M. Lemmens, editors), 12–14 July, Amsterdam, The Netherlands, pp. 747–754.

Zhu, Z., L. Yang, S.V. Stehman, and R.L. Czaplewski, 1999. Designing an accuracy assessment for a USGS regional land cover mapping program, *Spatial Accuracy Assessment—Land Information Uncertainty in Natural Resources* (K. Lowell and A. Jaton, editors), Sleeping Bear Press/Ann Arbor Press, Chelsea, Michigan, pp. 393–398.

———, 2000. Accuracy assessment for the U.S. Geological Survey regional land cover mapping program: New York and New Jersey region, *Photogrammetric Engineering & Remote Sensing*, 66(12):1425–1435.

(Received 23 May 2001; accepted 20 August 2001; revised 14 September 2001)